Probabilistic Visibility Forecasting Using Bayesian Model Averaging

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  - clear air RUC forecast, equal to a decaying exponential function of relative humidity (Smirnova et al 2000)

Visibility Data in PNW for 2007 and 2008

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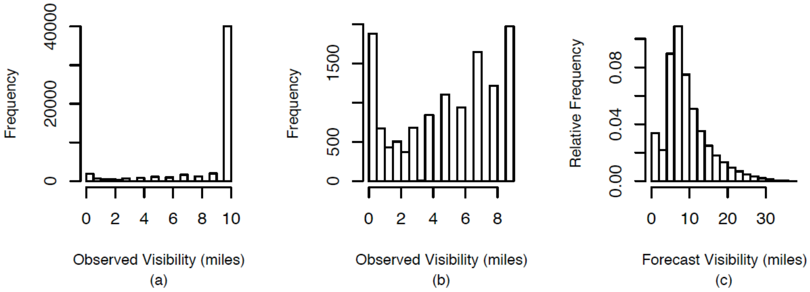

- 77% of obs are at 10 miles

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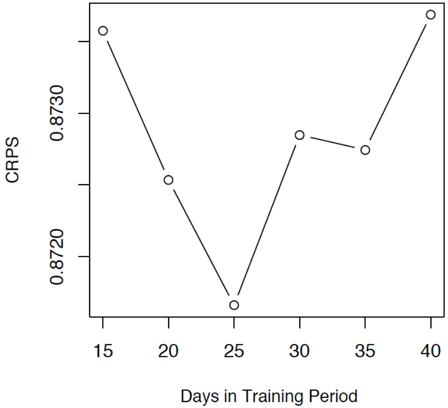

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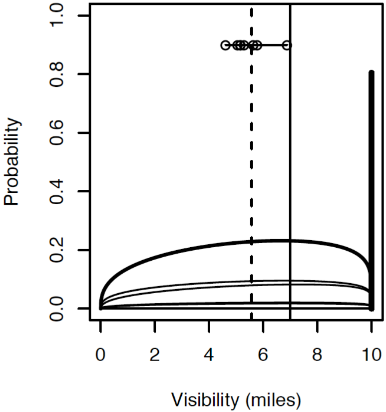

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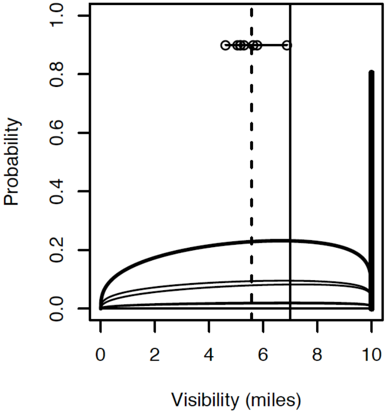

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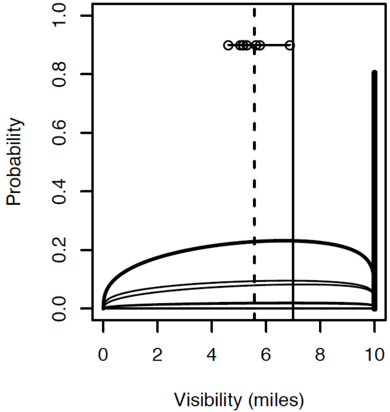

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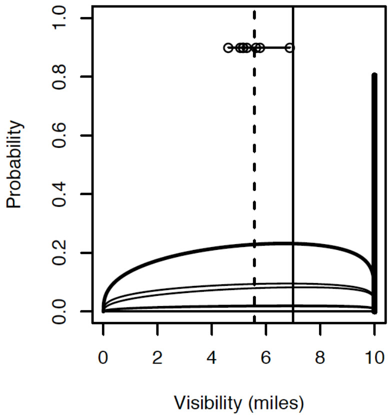

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- BMA 80% interval (dashed vertical lines): $[5.6, 10]$ miles

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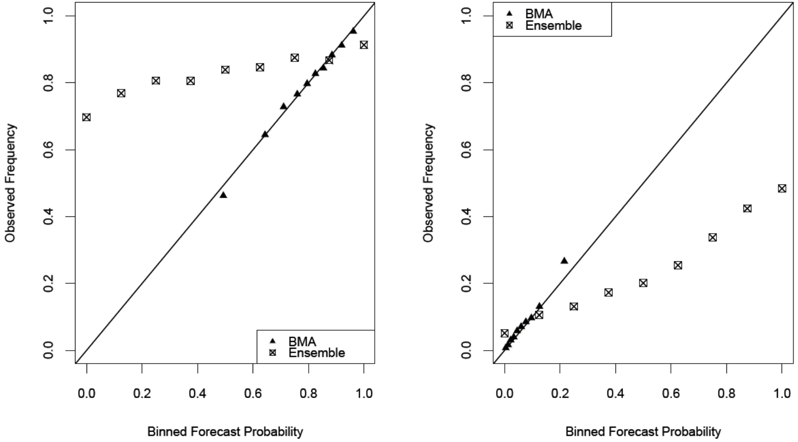

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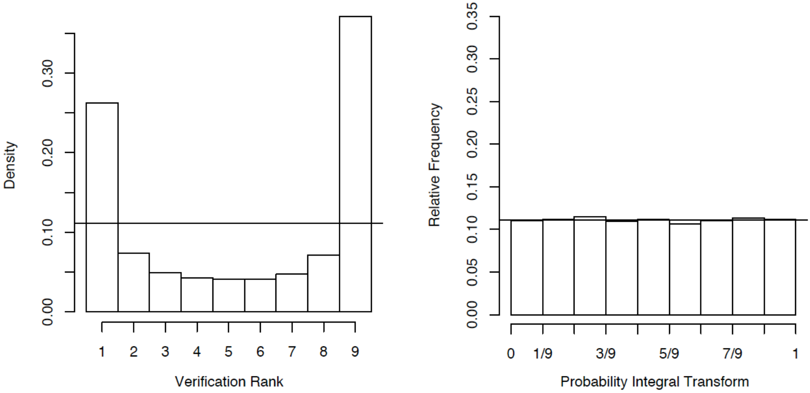

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